Design and Development of Decision Support Based Hybrid Recommender System

A
SYNOPSIS

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INTRODUCTION

The advent of recent information and communication technologies has significantly changed the way one can collect and access the information. Advancement of these technologies helps individuals and organizations in using this information to support their business decision-making activities.

The emphasis in information technology research deals with making the information universe friendly, understandable, and useful by filtering out noisy elements, finding useful nuggets of information on demand, and creating new knowledge.

The technologies to cope with the evolving information ecology can be categorized into four groups (Adomavicius & Tuzhilin, 2002):

- The technologies for discovering information say through search engines;
- The technologies for controlling and restricting the flow of information by using alerting systems;
- The technologies for understanding information by using data mining, and statistical tools; and
- The technologies to assist decision making.

The technologies for discovering, controlling and understanding information provide support for decision making through a recommender system or a decision support system.

A recommender system is an information filtering system that presents the user-relevant information by creating a user's profile and comparing it to the other existing reference characteristics stored in the database. It deals with the problem of information overload by filtering vital information fragment from dynamically generated information according to user’s preferences, interest, or observed behavior about an item (Balabanoviq & Shoham, 1997).

The *operational* and *technical* goals of recommender systems are:

- *Relevance:* i.e. to recommend items that are relevant to the user;

- *Novelty:* i.e. recommending the items that the user has not seen in the past;
- *Serendipity:* i.e. discovering somewhat unexpected recommendations; and
- *Increasing recommendation diversity:* i.e. ensuring that the user does not get repeated recommendation of similar items.

Aside from these concrete goals, a number of soft goals like providing overall user satisfaction, insights into the needs of the user, and help customize the user experience further, are also met by the recommender system.

1.1 Approaches of Recommender Systems

Most recommender systems take either of two basic approaches:

Collaborative Filtering

Collaborative filtering is a method of making automatic predictions (or filtering) about the interests of a user by collecting preferences from many users.

Collaborative filtering approach aggregates ratings, recognizes similarities between individuals, and generates recommendations based on inter-user comparisons (Ekstrand, Riedl & Konstan, 2011). It is assumed that the individual ratings represent fairly constant opinions which can be analyzed to provide a reasonable estimate of the actual individual preferences.

The main advantages of the approach are that it is simple as it focuses on only the item rated highly by peers that reduce workload, and it can be applied to almost any type of content.

Content based filtering

Content-based filtering methods are based on description of the items and a profile of the user's preferences. Keywords are used to describe the items. A user profile is then built to indicate the

type of item this user likes. In other words, these algorithms try to recommend items that are similar to those that a user liked in the past, or is examining in the present.

With the advancement of technologies more advanced methods like data mining, multi-criteria decision making, Geographic Information System and mathematical approaches are also used for generating powerful recommendations.

1.2 Types of Recommender Systems

A recommender system can be of following types:

1. Neighborhood-based Recommender System

These systems consider the preferences of the neighborhood users before making suggestions or recommendations to the active user. The system finds all the users similar to the active user who had similar preferences in the past, and then makes predictions regarding all unknown products that the active user has not rated but are being rated in their neighborhood.

Since similarity calculations are involved, these recommender systems are also called *similarity-based recommender systems*. Also, since preferences are considered collaboratively from a pool of users, these recommender systems are also called *collaborative filtering recommender systems*. In these types of systems, the main actors are the users, products, and user's preference information such as rating/ranking/liking towards the products.

The systems are based on the assumptions that the users with similar preferences in the past have similar preferences in the future, and the preferences of the users will remain stable and consistent in the future.

The Neighborhood-based systems can be classified as:

a. User-based collaborative filtering

The basic idea of these systems is that people with similar tastes in the past will like similar items in future as well.

Some disadvantages of these systems are

- The system suffers with performance if the user ratings are very sparse, which is very common in the real world where users rate only a few items from a large catalog;
- The computing cost for calculating the similarity values for all the users is very high if the data is very large; and
- If user profiles or user inputs change quickly then the similarity values have to be recomputed, resulting in a high computational cost.

b. Item-based collaborative filtering

In item-based collaborative filtering recommender systems, unlike user-based collaborative filtering, similarity between items is used instead of similarity between users, i.e. if a user liked item A in the past they might like item B which is similar to item A.

Item-based recommendation engines handle the shortcomings of user-based collaborative filtering by calculating similarity between items or products instead of calculating similarity between users, thereby reducing the computational cost. Since the item catalog does not change rapidly, re-computation is not required very often.

2. **Personalized Recommender System**

Personalized recommendation takes into consideration users' previous history for rating and predicting items. These systems take the personalized behaviour of the users. The system can be categorized as:

a. Content-based Recommender System

The Content-based Recommendation Systems recommend items similar to those that a user has liked in the past. These systems analyze a set of documents and/or descriptions of items previously rated by a user, and build a profile of user interests based on the features of the objects rated by that user. The recommendation process matches the attributes of the user profile against the attributes of a content object.

b. Context Aware Recommender System

These recommender systems consider the present state of the user (like location, time, mood, and so on), that define the context of the user to provide the relevant information and/or services to the user.

Since users have different needs in different contexts, these recommendation systems can capture the context information of the user and refine their suggestions accordingly. In order to discover customers' behavior, different data mining techniques are combined (Husain, Wei, Cheng & Zakaria, 2011; Jelassi, Ben & Mephu, 2013; and Lin & Wenzheng, 2015) with recommender system for effective information filtering.

Data Mining

Data mining is the process of selecting, discovering, and modeling high volume of data to find and clarify unknown patterns (Chye & Kee, 2004). It has become the area of growing significance because it helps in analyzing data from different perspectives and summarizing it into useful information.

The data sources for mining can include databases, data warehouses, the Web, other information repositories, or data that are streamed into the system dynamically. There are several data mining techniques:

Classification

Classification is the process of generating a function/model that describes and distinguishes data classes. The model is derived based on the analysis of the training data set (i.e., data objects for which the class labels are known) and is then used to predict the class label of objects for which the class label is unknown.

Feature selection

Feature selection is one of the most frequent and important techniques in data preprocessing. It is the process of detecting relevant features and removing irrelevant, redundant, or noisy data. This process improves predictive accuracy and increases comprehensibility.

Clustering

Clustering attempts to structure data vectors by grouping them together into clusters based on their similar properties and values optimally.

Association rules

Association Rule is a rule which implies certain association relationship among a set of objects in a database.

3. Model-based recommender systems

The main objective of the similarity-based approaches is to calculate the weights of the user's preferences for the products or product content and then use these feature weights for recommending items. These approaches have been very successful, but have some limitations:

- Since entire data has to be loaded into the environment for similarity calculations, these approaches are very slow to respond in real-time;

- The weights calculated are not learned automatically as with machine-learning applications; and
- The system is not able to draw any inference for the users/items about which sufficient information is not yet gathered. This is known as cold-start problem.

In order to address these limitations, model based recommender systems are developed to improve the performance of the recommendation engines.

Using the available historical data, a model is built with weights learned automatically. New predictions regarding the products are made using the learned weights and then the final results are ranked in a specific order before making recommendations.

The following approaches can be used to develop Model-based recommender systems:

Probabilistic approaches

In a probabilistic approach, a probability model is built using the prior probabilities from the available data, and a ranked list of recommendations is generated by calculating the probability of liking/disliking of a product for each user. The Naïve Bayes method is an example of this approach.

Machine learning approaches

Using historical user and product data, features and output classes are extracted to develop a model in this approach. A final list of ranked product recommendations can then be generated using this model. Many machine-learning approaches such as logistic regression, k-nearest neighbors, classification, decision trees, support vector machine, and clustering can be used for developing the model.

Mathematical approaches

In these approaches, the ratings or interaction information of users on products are assumed to be simple matrices. Mathematical approaches are applied on these matrices to predict the missing

ratings for the users. The most commonly used approaches are the matrix factorization model and single valued decomposition models.

4. Knowledge-Based Recommender Systems

Knowledge-based recommender systems deal with the cases in which ratings are not used for the purpose of recommendations. Rather, the recommendation process is performed on the basis of similarities between customer requirements and item descriptions, or the use of constraints specifying user requirements. In these cases, the item domain tends to be *complex* in terms of its varied properties, and it is hard to associate sufficient ratings with the large number of combinations at hand.

The process is facilitated with the use of *knowledge bases*, which contain rules and similarity functions to be used during the retrieval process.

Knowledge-based recommender systems can be classified on the basis of the interface type (and corresponding knowledge) as:

a. Constraint-based recommender systems

In constraint-based systems, users specify requirements or constraints (e.g., lower or upper limits) on the item attributes. Domain-specific rules are used to match the user requirements to item attributes. Such rules could take the form of domain-specific constraints on the item attributes. Furthermore, constraint-based systems often create rules relating user attributes to item attributes. In such cases, user attributes may also be specified in the search process. Depending on the number and type of returned results, the user might have an opportunity to modify their original requirements. This search process is interactively repeated until the users arrive at their desired results.

b. Case-based recommender systems

In case-based recommender systems, cases are specified by the user as targets. Similarity metrics are defined on the item attributes to retrieve similar items to these cases. The similarity metrics form the domain knowledge that is used in such systems. The returned results are often used as new target cases with some interactive modifications by the user. This interactive process is used to guide the user towards items of interest.

Note that in both cases, the system provides an opportunity to the user to change their specified requirements.

5. Demographic Recommender Systems

In demographic recommender systems, the demographic information about the user is leveraged to learn classifiers that can map specific demographics to ratings or buying propensities. Although demographic recommender systems do not usually provide the best results on a stand-alone basis, they add significantly to the power of other recommender systems as a component of ensemble models.

6. Multi-Criteria Recommender Systems

In many recommendation applications, users may be interested in items on the basis of different criteria. In such cases, the overall rating is often a poor reflection of the user's overall choices. These overall rating in a multi-criteria system may be either explicitly specified by users, or it may be derived with the use of a global utility function. In cases where an overall rating is specified by users, it is possible to learn a user-specific utility function with the use of linear regression methods. For cases in which the overall rating is not specified by users, the items can be ranked directly by integrating the predictions from the various criteria without computing an overall rating. In other cases, one can implicitly average over various criteria in order to create the overall rating. If needed, the various criteria may be weighted using domain-specific knowledge.

7. Hybrid recommender systems

Collaborative filtering systems and content-based recommender systems are effective and cater to a wide range of needs. They have quite successful implementations but each independently has its own limitations. A hybrid recommender system is formed by combining collaborative filtering with content-based methods to cope up with these limitations. The most common approaches followed for building a hybrid system are as follows:

Weighted method

In this method the final recommendations would be the combination, mostly linear, of recommendation results available from all the recommendation engines. At the beginning of the deployment of this weighted hybrid recommendation engine, equal weights will be given to each of the results from available recommendation engines, and gradually the weights will be adjusted by evaluating the responses from the users to recommendations.

Mixed method

The mixed method is applicable in places where the results can be from all the available recommenders. These are mostly employed in places where it is not feasible to achieve a score for a product by all the available recommender systems because of data sparsity. Hence recommendations are generated independently and are mixed before being sent to the user.

Cascade method

In this approach, recommendations are generated using collaborative filtering. The content-based recommendation technique is applied and then final recommendations or a ranked list will be given as the output.

Feature combination method

The feature combination method combines both a) user-Item preference features extracted from content based recommender systems and b) user-item ratings information, and considers a strategy to build hybrid recommender systems.

1.3 Evolution of recommender systems with technology

With the advancements in technology, recommender systems have been evolving rapidly. Recommender systems are moving from simple similarity-measure-based approaches to machine-learning approaches.

Mahout for scalable recommender systems

In order to build recommendation systems on huge supply of data, Mahout, a machine-learning library built on the Hadoop platform enables to build scalable recommender systems. It provides infrastructure to build and evaluate the different types of recommendation algorithms.

Apache Spark for real time recommender system

In order to build a system to handle very heavy computations and respond online, a system is required that is big-data compatible and processes data in-memory. The key technology in enabling scalable, real-time recommendations is Apache Spark Streaming, a technology that leverages scalability of big data and generates recommendations in real time, and processes data in-memory

Neo4j for real-time graph-based recommender systems

Graph databases have revolutionized the way people discover new products and information. The graph databases allow to store this information in graphs as nodes and edges (relations). In recent times, recommender systems powered by graph databases have allowed organizations to build suggestions which are personalized and accurate in real time. One of the key technologies enabling

real-time recommendations using graph databases is Neo4j, a kind of NoSQL. A NoSQL database, popularly known as not only SQL, provides a new way of storing and managing data other than in relational format such as columnar, graph, key-value pair store of data. This new way of storing and managing data enables to build scalable and real-time systems.

Literature Review

Recommender Systems provide users with suggestions for items which are likely to be of interest for them. The primary goal of recommender systems is to help users make good choices. Details on Recommender Systems can be found in Francesco, Lior, Bracha & Paul (2011); Portugal, Alencar & Cowan (2015); Beel, Gipp, Langer & Breitinger (2016); Tarus, Niu & Mustafa (2017); and Wasid & Ali (2017).

Christakou, Vrettos & Stafylopatis (2007) proposed a recommender system by combining content based and collaborating filtering to generate precise recommendations for movies. The content filtering is based on a trained artificial neural network representing individual user preferences. Arazy, Kumar & Shapira (2009) designed a social recommender system by integrating the relationship indicators between users and recommendation sources like homophily, tie strength, trust, and reputation. Serrano-Guerrero, Herrera-Viedma, Olivas, Cerezo & Romero (2011) proposed a fuzzy linguistic recommender system in which multi-granular fuzzy linguistic modeling was used to represent and handle flexible information by means of linguistic labels. Zhang, Zhou & Zhang (2011) developed tag-aware recommender systems and emphasized on the contributions from three mainstream approaches: network-based methods, tensor-based methods, and the topic-based methods.

Bao, Zheng & Mokbel (2012) proposed a location recommender system, which consists of two main parts: offline modeling and online recommendation. The offline modeling part models each individual's personal preferences with a weighted category hierarchy. The online recommendation part selects candidate local experts in a geospatial range that matches the user's preferences using a preference-aware candidate selection algorithm. Khalaji, Mansouri & Mirabedini (2012) designed a recommender system using association of complementary and similarity among goods and commodities, and offered the best goods based on personal needs and interests. Shishehchi, Banihashem, Zin, Noah & Malaysia (2012) developed a knowledge based personalized e-learning recommendation system based on ontology and discussed appropriate recommendation technique

based on learning system characteristics. Ullah et al. (2012) proposed Hybrid Recommender System that accounts item attributes similarity, user rating similarity, user demographic similarity and the temporal information to make recommendation for user at specific time.

Huang (2013) proposed a recommendation model to discover closed consensus temporal patterns, and developed a recommendation system to suggest a temporal relationship between the items. Kant & Bharadwaj (2013) developed a hybrid recommender system by using the fuzzy naïve Bayesian classifier based collaborating filtering and recursive methods for handling correlation-based similarity problems. Lu, Shambour, Xu, Lin & Zhang (2013) proposed an intelligent recommendation system prototype by using hybrid fuzzy semantic recommendation which combined item-based fuzzy semantic similarity and item-based fuzzy collaborative filtering similarity techniques. Romadhony, Al Faraby & Pudjoatmodjo (2013) designed a personal recommendation system that generates two types of recommendation: personal and item-based. User-based collaborative filtering was implemented to produce personal recommendation. A collaborative filtering was implemented for recommending items. Werner, Cruz & Nicolle (2013) presented a recommendation system, based on the semantic description of both articles and user profile. Zhang et al. (2013) developed a fuzzy-based telecom product recommender system which combines user-based and item-based collaborative filtering techniques with fuzzy set techniques and applies it to mobile product and service recommendation.

Aissi, Gouider, Sboui & Said (2015) proposed a spatial online analytical processing recommender system to exploit spatial data warehouses and retrieve relevant information by recommending personalized spatial multidimensional expressions queries. The approach detects the preferences and needs of spatial online analytical processing users using a spatiosemantic similarity measure. Bahramian & Abbaspour (2015) proposed a content-based recommendation system which uses the information about the user's preferences and points of interests and calculates a degree of similarity between them. Frikha, Mhiri & Gargouri (2015) presented a semantic social recommender system by employing user interest ontology and Tunisian Medical Tourism ontology. Social

recommendation algorithm is implemented in order to be used in a Tunisia tourism Website to assist users interested in visiting Tunisia for medical purposes. Madia, Thakkar & Makvana (2015) reviewed various approaches for solving cold start problem in recommender system for e-commerce application. Chen, Zheng, Zhu & Xiao (2016) proposed a recommender system with composite social trust networks. A composite trust-based probabilistic matrix factorization model was developed. Milli & Milli (2016) developed a recommender method considering that dissimilar users have dissimilar tastes, too and also proposed ontology based solution for cold start problem. Pham, Jung, Nguyen & Kim (2016) developed an ontology-based multilingual recommendation system using integrated data from linked open data to support user with different languages on movie domain.

Li & Yin (2017) proposed an iterative recommender system with correction propagation to assist multiple human annotators for debugging tracking results in a collaborative way. Majd & Balakrishnan (2017) a trust model for recommender agent systems based on reliability, similarity, satisfaction and trust transitivity. Akcayol, Utku, Aydoğan & Mutlu (2018) developed a weighted multi-attribute based recommender system using extended user behavior analysis. Azizi & Do (2018) implemented an item-based collaborative filtering recommender system that uses user interaction data and application change history information to develop a test case prioritization technique. Beutel et al. (2018) developed recurrent neural network based recommender system in use at YouTube. Choo et al. (2018) presented an interactive visual information retrieval and recommendation system for large-scale document discovery. Dhanda & Verma (2018) presented a personalized recommendation system for academic literature based on high-utility itemset mining technique.

Ding, Li, Jiang & Zhou (2018) summarized location-based social networks recommender systems from the perspective of three-dimensional relationship among users, locations, and activities. User, activity, and location are called objects, and recommender objectives are formed and achieved by mining and using such 3D relationships. Gilotte, Calauzènes, Nedelec, Abraham & Dollé (2018)

proposed a counterfactual estimator and provided a benchmark of the different estimators showing their correlation with business metrics observed by running online A/B tests on a large-scale commercial recommender system. Kartoglu & Spratling (2018) proposed two types of recommender systems based on sparse dictionary coding. Firstly, a predictive recommender system was developed to predict a user's future rating of a specific item. Secondly, a top-n recommender system was designed for generating the list of predicted items that may be most relevant to a user. Lecron & Fouss (2018) suggested a convex regularized optimization model to produce recommendations, which is adaptable, fast, and scalable. Reddy & Govindarajulu (2018) introduced a recommendation system for college/course selection. Sperlì et al. (2018) designed a recommender system for big data applications that is used for providing useful recommendations in online social networks.

Tsai & Brusilovsky (2018) designed a recommender system interface to help users explore the different relevance prospects of recommended items in parallel. Wu et al. (2018) proposed dual-regularized matrix factorization with deep neural networks recommender system to deal with problem of data sparsity. Zamani & Shakery (2018) developed a framework for content-based filtering system using the statistical language modeling framework and introduced a threshold optimization algorithm to find a dissemination threshold for making acceptance and rejection decisions for new published documents. Zhao, Yao, Song, Kwok & Lee (2018) applied meta-graph to heterogeneous information network based recommender system and solved the information fusion problem with a matrix factorization and factorization machine framework.

Recommender Systems have been proven to be valuable for coping with the information overload problem in several application domains. Porcel, Moreno & Herrera-Viedma (2009) and Liao, Hsu, Cheng & Chen (2010) developed recommender systems to recommend research resources in libraries. Lu, Shambour, Xu, Lin & Zhang (2010) developed a recommender system to support government for recommending the proper business partners (e.g., international buyers, agents, distributors, and retailers) to individual businesses (e.g., exporters). Lucas et al. (2013) implemented

a recommendation methodology by using classification based association in a recommender system for tourism. Paranjape-Voditel & Deshpande (2013) proposed a stock market portfolio recommender system based on association rule mining to analyze stock data and suggested a ranked basket of stocks.

Serrano-Guerrero, Romero & Olivas (2013) developed a recommender system to suggest personalized activities for each student in order to reinforce their competences in a subject by using fuzzy linguistic labels. Yuan, Zheng, Zhang & Xie (2013) presented a recommender system for both taxi drivers and people expecting to take a taxi, using the knowledge of passengers' mobility patterns and taxi drivers' picking-up/dropping-off behaviors learned from the GPS trajectories of taxicabs. Agapito et al. (2014) proposed a health recommendation system for the adaptive delivery of nutrition contents both to healthy and chronically ill tourists in order to improve their quality of life by combining the needs of leisure with health benefits. Esteban, Tejeda-Lorente, Porcel, Arroyo & Herrera-Viedma (2014) presented a health recommender system to provide personalized exercises to patients with low back pain problems and to offer recommendations for their prevention. Ansari, Moradi, NikRah & Kambakhsh (2016) presented a hybrid and context-specific recommender system (CodERS) for our interactive programming e-learning system, CodeLearnr, and provided an overview on its features including conceptual architecture, workflow and sample outputs. Guo et al. (2016) developed a recommender system for identifying key opinion leaders for any specific disease with health care data mining.

Bocanegra, Ramos, Rizo, Civit & Fernandez-Luque (2017) investigated the feasibility of building a content-based recommender system that links health consumers to reputable health educational websites for a given health video from YouTube. Katarya &Verma (2017) focused on the movie recommendation systems to suggest recommendations through data clustering and computational intelligence. Deldjoo et al. (2016) proposed a content-based recommender system to automatically analyze video contents and extract a set of representative stylistic features (lighting, color, and

motion) grounded on existing approaches of applied media theory. Afolabi (2018) developed a Viable Architecture for the Integration of a Recommender System and Mobile Solution for the Management of HIV/AIDS. Albatayneh, Ghauth & Chua (2018) introduced a recommendation architecture for recommending interesting post messages to the learners in an e-learning online discussion forum based on a semantic content-based filtering and learners' negative ratings. Angskun & Angskun (2018) focused on finding a way to personalize attraction recommendations for travelers. The objective was to find an accurate way to suggest new attractions to each traveler based on the opinions of other like-minded travelers and the traveler's preferences. Appalla, Selvaraj, Kuthadi & Marwala (2018) proposed two algorithms, the hybrid fuzzy-based matching recommendation algorithm and collaborative sequential map filtering algorithm to assist users on their individual as well as collaborative learning methods for accessing learning resources.

Logesh, Subramaniyaswamy & Vijayakumar (2018) developed an intelligent real-time user-specific travel recommender system by incorporating users' social network profile and current location using global positioning system data for travel recommendation generation. Okhdar & Ghaffari (2018) developed an English vocabulary learning recommender system based on sentence complexity and vocabulary difficulty. Son & Kim (2018) proposed a recommendation system for academic papers based on multilevel citation networks that compares all the indirectly linked papers to the paper of interest for inspecting the structural and semantic relationships among them.

Different methods/models are also developed by researchers for implementing recommender systems. El Helou, Salzmann & Gillet (2010) discussed the 3A (3A entities- actors, assets, and activities) recommender system that targets computer supported collaborative learning and computer-supported collaborative work environments. The proposed system models user interactions in a heterogeneous graph. Ma, Zhou, Lyu & King (2011) attempted to combine a probabilistic matrix factorization method and social context/trust information for recommendation making. Birtolo & Ronca (2013) proposed two clustering filtering algorithms: item-based fuzzy clustering collaborative filtering and trust-aware clustering collaborative filtering for high level

recommendation for different users. Yu, Yamaguchi & Takama (2013) proposed a weight based recommendation method for social media, which usually has only the personal items uploaded by the users. Nilashi, bin Ibrahim & Ithnin (2014) proposed recommendation methods using adaptive neuro-fuzzy inference systems and self-organizing map clustering to improve predictive accuracy of criteria collaborating filtering. Ren, Lü, Liu & Zhang (2014) developed a recommendation method called directed weighted conduction method considering the heat conduction process on a user–object bipartite network with different thermal conductivities. Son (2014) presented a systematic mathematical definition of fuzzy recommender system including theoretical analyses of algebraic operations and properties. The authors also proposed a hybrid user-based fuzzy collaborative filtering method that integrates the fuzzy similarity degrees between users based on the demographic data with the hard user-based degrees calculated from the rating histories into the final similarity degrees. Zhang, Liu, Gui, Wei & Ma (2014) proposed a new prediction score model for the memory-based method and a differential model that considers the adjustment process after the training process in the existing matrix factorization methods.

An architecture that enables a representation of user preferences and manipulates relevant services description of available services was developed by Manqele, Dlodlo, Coetzee, Williams & Sibiya (2015). An algorithm is also derived from the architecture that contributes towards addressing the service selection. Sheugh & Alizadeh (2015) presented an extended Pearson correlation coefficient measure for cases where similarity between users does not exist. Experimental result on the film trust data set demonstrated that the proposed method is better than traditional Pearson correlation coefficient. Heitmann & Hayes (2016) introduced SemStim, an unsupervised graph-based algorithm that addresses the cross-domain recommendation task. In this task, preferences from one conceptual domain (e.g. movies) are used to recommend items belonging to another domain (e.g. music). Lu, Pan, Li, Jiang & Yang (2016) proposed a Collaborative Evolution model, which learns the evolution of user's profiles through the sparse historical data in recommender systems and outputs the prospective user profile of the future. Mediani & Abel (2016) proposed a semantic

recommendation approach of the pedagogical resources within learning ecosystem. This approach was based on a voting system that enables each member of the ecosystem to assess the appropriateness of one or more pedagogical resources found in his/her sharing space about a specific subject. Zhu, Hao, Chi & Du (2016) applied Labeled-LDA in user preference learning and local features inference processes. The approach helped in making recommendations even when users are in a new city and have little information about it.

Nizamkari (2017) proposed a scalable graph-based collaborative filtering recommendation algorithm, improved using trust to solve service selection problem. Using this recommender the best rated service provider could be selected. Sohail, Siddiqui & Ali (2017) proposed an authority's recommendation approach which exploits ranking of the books by different top-ranked universities. These rankings are aggregated using ordered weighted aggregation, a fuzzy averaging operator. Thotharat (2017) presented ontology based recommender system for Thai local products. With the designed ontology, products were mapped to the schema for realizing their properties. Wasid & Ali (2017) extend two-dimensional recommender systems by incorporating contextual information into fuzzy collaborative filtering user profile through contextual rating count approach and genetic algorithm. Geuens, Coussement, & De Bock (2018) proposed a decision support framework to help e-commerce companies select the best collaborative filtering algorithms for generating recommendations on the basis of online binary purchase data. Hu, Liang, Kuang & Honavar (2018) proposed an effective and accurate two-staged user similarity based top-*N* recommendation approach, which combines user clustering and top-*N* ranking into a recommender system for large mobile in-app advertising. Hamidi & Mousavi (2018) proposed a database sampling framework that aims to minimize the time necessary to produce a sample database and argued that the performance of current relational database sampling techniques that maintain the data integrity of the sample database is low and a faster strategy needs to be devised.

Khedr, Idrees, Hegazy & El-Shewy (2018) presented a configurable approach for recommendations which determines the suitable recommendation method for each field based on the characteristics of its data. Jiang, Liu, Fu, Wu, & Zhang (2018) proposed a Bayesian personalized ranking based machine learning method to learn the weights of links in a personalized recommender system. Lian et al. (2018) proposed a scalable implicit-feedback-based content-aware collaborative filtering framework to incorporate semantic content. The authors also developed an efficient optimization algorithm, scaling linearly with data size and feature size, and quadratically with the dimension of latent space. Nilashi, Ibrahim & Bagherifard (2018) developed a hybrid recommendation method based on collaborative filtering approaches using dimensionality reduction and ontology techniques. Tsai (2018) proposed a visual diversity-enhanced interface that supports the user to inspect and control the multi-relevance recommendations. The goal was to let the users explore the different relevance prospects of recommended items in parallel. Zhang, Fan & Wang (2018) proposed a recommendation approach to handle large-scale data efficiently that contributes to the fields of recommender systems and big data analytics.

Motivation

The above literature review revealed the following:

- Most of the previous researches have focused on recommendation techniques and algorithms for information filtering, and less attention has been devoted to the decision making processes supported by the system (Chen et al., 2013).

  A primary function of recommender systems is to help people make good choices and decisions. But research on recommender systems has focused mainly on (a) ways of eliciting and modeling users' preferences and (b) algorithms for identifying items that a user is likely to evaluate positively. Less attention has been given to the decision making processes of users that are triggered or supported by the system.

- In many cases where a wider variety of inputs is available, one has the flexibility of using different types of recommender systems for the same task. In such cases, opportunities exist for hybridization, where various aspects from different types of systems are combined to achieve the best of all worlds (Zhang, Min, He & Xu, 2015).

  Hybrid recommender systems are closely related to the field of ensemble analysis. Ensemble-based recommender systems are able to combine not only the power of multiple data sources, but they are also able to improve the effectiveness of a particular class of recommender systems.

- Despite wide literature on the topic, using multiple data sources of different types as the input has not been widely studied (BellogíN, Cantador & Castells, 2013).

  Recommender systems can benefit from the high availability of digital data to collect the input data of different types which implicitly or explicitly help the system to improve its accuracy.

PROPOSED WORK

The focus of this research study is to design and develop decision support based hybrid recommender system to generate powerful recommendations which will help in effective decision making.

Objectives of the study

1. Design and development of a Hybrid Recommender System;
2. Development of recommendation tools by combining users preferences and users behaviors;
3. Designing the recommendation database infrastructure; and
4. Integrating decision support system with recommender system.

Methodology

1. **Development of the hybrid Recommender System using ensemble approach:**

   This research study will be devoted to the study of hybrid recommendation methods. Techniques like multi-criteria decision making, case based reasoning, and/or data mining will be integrated for identifying patterns from multidatabases (Object-relational database or Spatial and temporal data, the one best suited in this study will be taken).

2. **Integrating Decision Support System with Recommender System:**

   A decision support system will be integrated with recommender system for generating decision support based recommendations using MATLAB/.Net Framework.

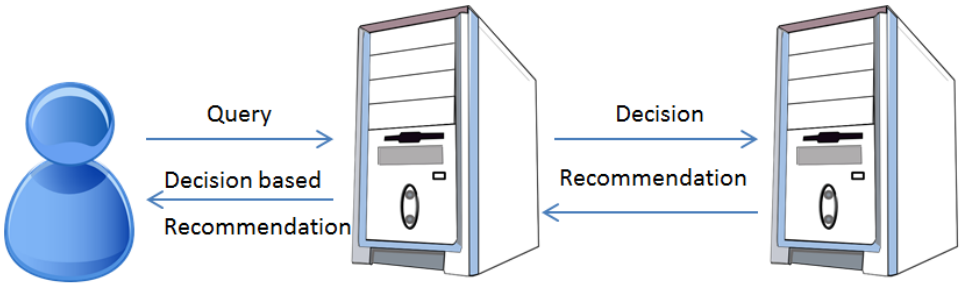

Figure 1: Proposed Decision Support based Recommender System

3. **Selecting and creating a dataset**

   This study will deal with the variables like cost, time, location, and others based on the application area chosen for the study (Education System, Health Care, or Tourism).

   Having defined the goals, the data that will be collected for decision support based information filtering. This includes finding out what data is available, obtaining additional necessary data, and then integrating all the data into one data set, including the attributes that will be considered for the process. The application domain for this study will be one of the following:

   a. Generating decision support based information for higher education (by developing a University Recommender System in general and for Dayalbagh Educational Institute (Deemed University), Agra in perticular as a case study); or
   b. Generating decision support based information for tourism (taking Agra as a case study)

Stages of building proposed system

From software engineering point of view, component based software development process model will be used for developing the system. The phase-wise description of development process is as follows (Figure 2):

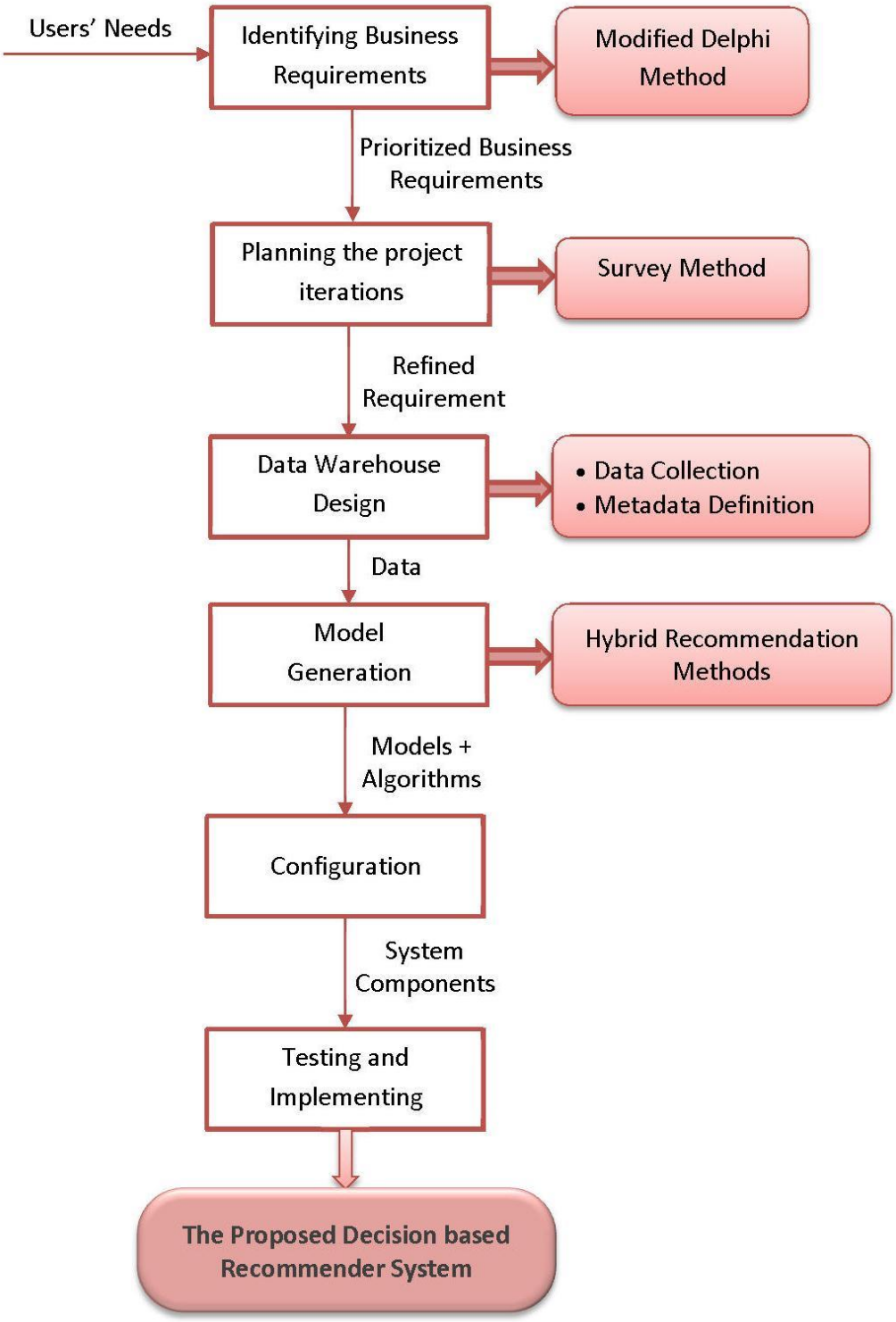

Figure 2: Stages of development

1. **Identifying Business Requirements:** This step includes identifying business requirement. On the basis of identified user's requirements, the priorities will be established, depending on their relative importance. This priority list will used to establish the subsequent iterations of recommender system development.

2. **Planning the project iterations:** Depending on the priorities established in the stage of business requirement identification. The identified business and technical requirements will be refined for recommender system development and implementation.

   The preliminary analysis made in the previous stages will be detailed. All the constraints imposed by the source systems will be identified.

3. **Data warehouse design:** The relevant data will be collected from primary and secondary sources. The data warehouse will be designed by defining the metadata, and updating the data source to include all the information necessary for the implementation.

   Useful data from the data resources will be extracted, transformed, and loaded to data warehouse. The extraction of data is determined by the recommender.

4. **Model Generation:** According to the requirements of recommendation, models are generated using corresponding recommendation algorithms, and are stored in models database.

5. **Configuration:** Different models and algorithms are deployed in various recommendation strategies to supply different kinds of services.

6. **Decision Support based Recommender System testing and implementation:** Once the planning and design stages are completed, the current iteration for recommender system implementation will start. In this stage, the development and testing environments will be established, and the system will be implemented.

The Architecture of the proposed Decision Support based Recommender System

The components of the proposed System will be:

i. **Recommendation System Database:** This component will store the dataset relevant to the application domain. It will establish a one to one corresponding relationship with recommendation engine, and will be managed by recommendation management module.

ii. **Data Management:** This component will administrate the dataset in the data warehouse including generating, deleting and modifying recommendations, and loading, deleting, and updating the dataset.

iii. **Recommendation Models Database:** The recommendation models will be stored in this component to supply different recommendation services, and build multiple recommendation models to generate different kinds of recommendation.

iv. **Recommendation Engine:** Recommendation engine will help in generating recommendations by using the developed recommendation algorithms and models.

The architecture of the proposed system will be as shown in Figure 2.

Figure 2: Architecture of the proposed system

The capabilities of the proposed system will be

- The ability to scale to large volumes of data
- Improved performance by combining some techniques.
- Generate faster, efficient & precise recommendations according to user's interest.
- Ensure that the user does not get same (repeated) recommendations.
- Availability of a wide variety of viewing and analysis tools to support different user communities

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